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Wholesale Electricity Price Volatility and Price Bounds: A Market Comparison

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Abstract

Due to high volatility and frequent price spikes in wholesale electricity market prices, market regulators often impose price bounds on auction and final market prices. This paper applies a model-free intraday-range measure and ARMA-EGARCH(1,1) models to wholesale electricity price data collected from seven markets in the United States and Europe to measure and compare volatilities across the seven markets and the effects of exogenous amendments to price bounds in a subsample of three markets. The paper concludes that the wider a market's imposed price bounds, the higher the price volatility. Conclusions also suggest that exogenous price bound changes have more significant effects in markets with tighter imposed bounds and that changes made to locational marginal price bounds have greater effects on price behavior than do changes made to energy offer price bounds. Conclusions add to emerging research about the effects of price bounds on electricity price volatility and are relevant for policy makers and market participants concerned with price volatility.

Keywords: wholesale electricity market, price volatility, intraday range, price bounds

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1. Introduction

Since the liberalization of the wholesale electricity industry in the 1990s, electricity generators and consumers, risk managers, traders, policymakers, and academics have paid special attention to the commodity's high levels of volatility. Electricity prices exhibit volatility multiple times higher than that of other energy commodities (see: Ullrich, 2012; Higgs and Worthington, 2008; Dahl, 2015) like natural gas, crude oil, and coal, and are characterized by frequent price spikes. In an effort to mitigate the potentially damaging effects of high volatility and price spikes – measures of market risk – market regulators impose bounds (price caps and floors) on wholesale electricity market prices. I contribute to a nascent line of research about the effects of imposed price bounds on market price volatility by calculating a model-free intraday range measure as a proxy for volatility and applying the ARMA-EGARCH model specification to price data.

I have gathered historical time series day-ahead wholesale electricity price data from seven markets in both the United States and Europe whose imposed price bounds differ. The day-ahead market establishes, a day before, 24 market clearing prices for contracts with physical delivery of electricity the next day. This paper finds, after calculating intraday range values, a positive relationship between the width of a market's imposed price bounds and that market's price volatility. Further, ARMA-EGARCH model results suggest that a market's price bounds change the degree to which different types of amendments to price bounds affect volatility.

The order of this paper is as follows: Section 2 explores justifications for price bounds and offers a review of literature about their roles in wholesale electricity markets, Section 3 provides a description of the data and its characteristics and the calculation and interpretation of intraday range in all seven markets, Section 4 describes the methodology and application of the

ARMA-EGARCH models along with major empirical conclusions, and Section 5 concludes and discusses implications of the results.

2. Price Bounds: Description, Justifications, and Related Literature

Table 1 below shows regulator-imposed Energy Offer (EO) and Locational Marginal Price (LMP) price bounds in effect for the seven markets, and the locations these markets serve, studied in this paper. Market regulators also impose scarcity price limits and other bounds like Violation Relaxation Limits (VRLs) to clear market prices in rare instances of *extreme* demand/supply movements. EO and LMP price bounds are more relevant during normal day-ahead trading environments and are thus the subject of this research.

Table 1: Energy Offer and LMP Price Bounds

Market	Location	EO floor/cap	LMP floor/cap
	USA	**($/MWh)**	**($/MWh)**
CAISO	California	-150/1,000	none
ERCOT	Texas	none/9,000	-251/none
MISO	Midcontinent	-500/1,000	-500/3,500
PJM	Central-East	no floor/2,000	none
	Europe	**(€/MWh)**	**(€/MWh)**
Nord Pool	Nordic region	-500/3,000	-500/3,000
OMIE	Spain	0/180.3	0/180.3
EPEX Spot	Central-West	-500/3,000	-500/3,000

Source: market websites and e-mail correspondence with industry professionals from the seven markets; Information as of Oct. 26, 2016

I consider the OMIE market to have the "tightest" – or most restrictive – width of LMP and EO price bounds, followed by the Nord Pool, EPEX Spot, MISO, ERCOT, and CAISO markets, and the PJM market which I consider to have the "widest" – or least restrictive – imposed combination of price bounds.

Not all markets impose price bounds and justifications for setting and not setting price bounds differ. Of the seven total markets, the CAISO and PJM markets do not enforce maximum or minimum limits on LMP prices. Justifications for foregoing such limits include[1]:

a.) Price signals: the market clearing price algorithm functions best with true price signals and market participants rely on accurate price signals when making investment decisions. Limiting LMP price behavior via price bounds perverts price signals and the overall efficiency of the market.

b.) Laissez-faire philosophy: the market itself can and should determine the most efficient outcome of price. All information is priced into LMP prices in the absence of price bounds and interfering in the natural working of the market can destabilize the market.

c.) Other limiting mechanisms: LMP price bounds are redundant because other mechanisms like EO bounds and VRLs are triggered if the LMP price becomes too high in the course of normal market functioning.

The remaining five markets in this study do impose LMP price bounds. These markets put forth the following justifications for enforcing LMP bounds[2]:

a.) No perfect market: the wholesale electricity market is neither a voluntary nor perfectly competitive one. Consumers cannot exit the market when prices are exorbitant and there is no substitute for electricity. Further, suppliers cannot differentiate among consumers based on the electricity reliability they demand. Price bounds act to neutralize these market imperfections.

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[1] Source: e-mail correspondences with industry professionals from the SPP (Southwest Power Pool) and PJM markets, provided in Appendix A.

[2] Source: e-mail correspondences with industry professionals from the Nord Pool, MISO, SPP, IESO (Independent Electricity System Operator, Ontario), and OMIE (Spain) markets, provided in Appendix A.

b.) Encourage market functioning: by establishing upper and lower bounds, market participants are aware that prices will remain within a known limit, which removes uncertainty and encourages a more natural functioning of the market.

c.) Proper algorithm function: the market clearing algorithm operates most efficiently when upper and lower bounds are imposed on the parameters and avoids calculations based on supply and demand curves when upper price bounds are reached.

d.) Other: markets implement price bounds to remain consistent with neighboring markets or because historical maximum prices have not reached the maximum limit. In some markets these reasons are reasons enough to maintain price bounds.

2.1. EO versus LMP price bounds

Market regulators implement both EO and LMP price bounds – and not simply one – because there are instances wherein natural market forces push final LMPs above EO price bounds. Consider first the following components of the LMP:

$$LMP = MCP + congestion\ costs + transmission\ costs \tag{1}$$

Market operators oversee wholesale auction markets wherein electricity generators and consumers "offer" or bid quantities and prices of electricity to be produced and consumed. An algorithm then matches the resulting market supply and demand curves to establish an hourly "market clearing price" (MCP) - the least expensive price which clears the market and is subsequently paid to (by) every supplier (consumer) of electricity. In the process of delivering electricity to market consumers, at different locations called "nodes," "zones," or "hubs," transmission line capacity limits may be reached ("congestion costs") and a percentage of electricity will be lost in the form of heat ("transmission costs"), meaning that the final price consumers pay – the LMP – is a product of the system-wide MCP plus other costs specific to a consumer's location.

It follows that the MCP is capped at the EO price bound. However, when congestion costs or transmission losses are greater than zero, final LMPs may surpass EO price bounds such that other (LMP) price bounds then become necessary. In this way, EO bounds prevent resource suppliers from exercising market power by limiting the price they bid to the electricity auction market while LMP bounds limit the final price of electricity at a specific trading location. Both play important roles and are examined in more detail throughout this paper.

2.2. Literature on price bounds and price behavior

Literature suggests that price bounds influence the investment decisions and behaviors of market participants, and ultimately the final prices, in wholesale electricity markets. Electricity generators can only justify investing in new capacity for future generation if they are certain that they will be able to recover the costs of such investments. Joskow (2006) explains that a "missing money" problem arises when the cost of producing electricity outweighs the revenues a generator receives from selling that electricity. Price caps have the potential to worsen this cost/revenue gap because they limit how high price spikes can climb, a major source of revenues for producers (see also: Higgs and Worthington (2008)). Zoettle (2008), Higgs and Worthington (2008), Deng and Oren (2006), Tishler, Milstein, and Woo (2008), and Ford (1999) also comment on the influence price caps have on limiting cost-recovering price spikes and therefore capacity investment. In the extreme, when price bounds are too restrictive, electricity generators decrease capacity investment causing higher and more volatile electricity prices in the future.

Robinson and Baniak (2002) studied the behaviors of electricity producers in the English and Welsh electricity pools and found that volatility under price cap regimes actually increased due to price manipulation on the part of producers. By increasing the price risk (or volatility) on electricity contracts they sold, producers were able to maintain their revenues under the price cap regime. Gülen and Soni (2013) looked at the ERCOT market in Texas and found that there were more relative extreme price spikes under lower price cap regimes, suggesting that electricity producers were able to change their production behavior, in reaction to price bound changes, in order to extract more rents via price spikes.

Simshauser (2014), in his research of price caps in Australia, goes on to suggest that price caps, when imposed on competitive markets, can disrupt their natural functioning. Tishler et al. (2008) apply a two-stage, competitive electricity market model on Israeli electricity data and find that as they apply and tighten an imposed price cap, a reduction in system reliability follows as electricity outages increase. Interpreted in this way, price caps have the potential to significantly influence final market and price outcomes.

Further, the relationship between price bounds and price volatility has been (indirectly) studied in previous literature, with mixed results. Tashpulatov (2013) applies an AR-ARCH model to prices in the England and Wales wholesale electricity market during different regulator-applied price cap and divestment regimes and finds, among other conclusions, that the imposed price caps did lower the overall price level of the market but increased price volatility. Robinson and Baniak (2002) and Gülen and Soni (2013) make similar conclusions about price caps and price volatility throughout their research. On the other hand, research by Hobbs, Iñon, and Stoft (2001), Joskow (2006), Higgs and Worthington (2008), Deng and Oren (2006), Tishler et al. (2008) and Ford (1999) find that relationships between price bounds and price volatility are positively correlated. Hobbs et al. (2001) use a simple model and historical PJM market load data to simulate the operations of different market structures and conclude that an installed capacity (ICAP) market structure with imposed price caps functions reliably and with fewer price spikes and lower price volatility.

Previous research points to the importance of price bounds in market designs but offers mixed conclusions about their effects on wholesale electricity price volatility, leaving room for further research. My work extends beyond past literature by specifically exploring the direct relationship between wholesale electricity price bounds and price volatility. In doing so, I isolate and examine the effects of *exogenous* changes to price bounds, study an extensive sample of seven electricity markets which allows for inter-market comparisons, and employ a variety of volatility measures simultaneously. I do not ignore or treat negative prices as has been done in previous research (eg. by winsorization transformation). To the best of my knowledge such a focused study of price bounds and volatility is absent in previous research, making my contributions both relevant and warranted.

3. Data, Descriptive Statistics, Seasonality Correction, and Intraday Range (IDR)

The data used for the purpose of this research was collected from the *Bloomberg Terminal*. Day-ahead wholesale electricity prices were collected from hubs – price points where electricity is frequently and liquidly traded – in four centralized markets in the United States and three in Europe: CAISO, ERCOT, MISO, PJM, the Nord Pool, OMIE, and EPEX Spot. The Nord Pool is a centralized pool design, while the other six markets are centralized exchanges. All seven markets are independently operated and are some of the largest and most liquid in the world, making them good candidates for study.

Price data for all markets are in two frequencies: hourly and daily. In the application of the ARMA-EGARCH(1,1) models, hourly prices for the EPEX Spot, PJM, and ERCOT markets were transformed to daily prices by simply taking the arithmetic average of the hourly prices over a given day. Hourly and daily frequencies are applied throughout.

Descriptive statistics of prices from the seven markets are displayed in Table 2 below. Electricity is a non-storable commodity meaning that prices are cleared in close to real time. Supply and demand curves are highly inelastic because electricity is costly and inflexible to produce and distribute, has no real substitute, and is a necessary good. For these reasons, prices often exhibit high volatility, frequent large price spikes, seasonality, and negative prices. Statistically speaking, they exhibit mean reversion, stationarity, asymmetric movements, and are characterized by fat-tailed distributions.

In Table 2, maximum prices are high and skewness and excess kurtosis values, in all markets except OMIE, are well above zero indicating frequent price spikes in heavy tails. Sudden shocks to inelastic supply and demand curves are reflected immediately in the price (no smoothing with inventories), often resulting in price spikes as high as 94 standard deviations above the mean in some markets.[3] Positive skewness is explained by asymmetric price movements, or an *inverse* leverage effect – as opposed to a normal leverage effect in equity markets – where positive price spikes are more extreme than negative ones. Note that outliers in the series do not bias and are maintained in model-free calculations though are later corrected in the ARMA-EGARCH(1,1) application.

Negative prices are evident in three of the seven markets and are an increasingly common phenomenon in markets which allow them. The addition of renewable energy to generation mixes has shifted inflexible electricity supply curves outwards, making negative prices more frequent.

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[3] Author's own calculation, using EPEX Spot market data

See Ullrich (2012), Knittel and Roberts (2005), Geman and Roncoroni (2006), Goto and Karolyi (2004), Escribano, Peña, and Villaplana (2011), and Lucia and Schwartz (2002) for exhaustive analyses of electricity price behavior including seasonality, mean reversion, skewness and kurtosis, and spikes, and appropriate model applications to such behavior.

3.1. Correction for seasonality

Raw and seasonally corrected price data are used throughout the paper. Wholesale electricity prices exhibit hourly, daily, and monthly seasonality: retail electricity use is higher in the early morning and evening than during nighttime hours (on-peak vs. off-peak hours) and is higher during the week than it is on weekends. Electricity demand also varies with monthly weather patterns as consumers use heat in winter months and air conditioning during summer months.

I apply dummy variables to correct for the deterministic component of seasonality in the prices. For hourly data, I employ hourly, weekday, and monthly dummy variables to compute a seasonality-corrected price, $price_{corrected_t}$. For daily price data the correction is the same though without hourly dummy variables. This approach follows the method of Pereira, Pesquita, Rodrigues, and Rua (2016), i.e.,

$$price_{raw_t} = c + \sum_{i=2}^{24} \varphi_i \, h_{it} + \sum_{j=2}^{7} \delta_j \, d_{jt} + \sum_{k=2}^{12} \psi_k \, m_{kt} + \varepsilon_t \qquad (2)$$

$$price_{corrected_t} = price_{raw_t} - \sum_{i=2}^{24} \hat{\varphi}_i \, h_{it} - \sum_{j=2}^{7} \hat{\delta}_j \, d_{jt} - \sum_{k=2}^{12} \hat{\psi}_k \, m_{kt} \qquad (3)$$

where $price_{raw_t}$ is the original hourly/daily price data in levels and $\hat{\varphi}_i$, i = 2,…,24, $\hat{\delta}_j$, j = 2,…,7, and $\hat{\psi}_k$, k = 2,…,12 are the coefficient estimates for the hourly, weekday, and monthly dummy variables, respectively.

Table 2: Descriptive Statistics, A.) Hourly, raw B.) Hourly, seas. corrected C.) Daily, raw D.) Daily, seas. corrected

A.)	**CAISO**	**ERCOT**	**MISO**	**PJM**	**Nord Pool**	**OMIE**	**EPEX Spot**
Date	3/23/09 - 10/26/16	12/1/10 - 10/26/16	4/1/05 - 10/26/16	1/1/05 - 10/26/16	1/2/00 - 10/26/16	7/1/07 - 10/28/16	8/1/00 - 10/26/16
Hub/Zone	NP-15 Zone	North Zone	Michigan Hub	Western Hub	SE3	Spain	Phelix Hub
No. Obs.	66600	51768	101448	103608	147432	81792	142344
Max ($,€)	472.94	2635.64	472.29	949.08	1400.11	145.00	2436.63
Min ($,€)	-13.94	1.48	-70.51	0.00	0.00	0.00	-500.02
Mean ($,€)	34.59	32.28	38.77	46.47	34.38	45.35	37.88
Median ($,€)	33.79	26.36	21.43	38.96	31.62	46.00	34.43
Std. Dev. ($,€)	12.46	59.54	21.96	29.34	19.97	16.59	25.49
Skew.	1.90	27.21	3.30	6.12	18.29	-0.24	16.17
Exc. Kurt.	39.42	926.52	25.88	96.23	1029.95	0.75	1074.44
B.)							
Max ($,€)	465.37	2555.77	444.39	919.37	1390.38	140.42	2397.89
Min ($,€)	-13.85	-52.18	-75.06	-14.95	-6.36	-7.61	-494.87
Mean ($,€)	32.26	16.08	22.83	30.50	32.71	49.78	19.08
Median ($,€)	31.37	14.68	19.08	25.55	30.26	50.14	16.84
Std. Dev. ($,€)	10.52	57.67	19.35	26.93	19.33	14.35	22.92
Skew.	2.79	27.45	3.74	6.86	19.53	-0.13	21.05
Exc. Kurt.	70.61	947.44	36.70	120.53	1138.76	0.63	1579.83
C.)	**CAISO**	**ERCOT**	**MISO**	**PJM**	**Nord Pool**	**OMIE**	**EPEX Spot**
Date	3/23/09 - 10/26/16	12/1/10 - 10/26/16	4/1/05 - 10/26/16	1/1/05 - 10/26/16	1/2/00 - 10/26/16	7/1/07 - 10/28/16	8/1/00 - 10/26/16
No. Obs.	2775	2157	4227	4317	6143	3408	5931
Max ($,€)	126.39	483.55	367.06	558.74	505.68	93.11	301.54
Min ($,€)	0.54	11.14	12.71	17.42	3.51	0.00	-56.87
Mean ($,€)	34.59	32.28	38.77	46.47	34.38	45.35	37.88
Median ($,€)	33.78	28.59	34.56	40.26	31.71	46.05	35.03
Std. Dev. ($,€)	8.95	26.35	16.24	23.52	16.95	13.69	17.74
Skew.	0.86	9.95	4.16	6.52	5.44	-0.36	2.18
Exc. Kurt.	5.05	126.12	50.64	98.87	112.90	0.84	16.89
D.)							
Max ($,€)	124.96	472.68	357.34	541.18	501.72	96.85	284.09
Min ($,€)	7.50	-15.15	6.95	6.03	4.49	0.31	-74.28
Mean ($,€)	35.71	23.81	33.43	40.99	35.32	48.06	25.54
Median ($,€)	34.40	21.80	30.22	36.21	32.91	48.48	23.24
Std. Dev. ($,€)	8.50	24.96	15.52	22.81	16.52	12.62	16.45
Skew.	1.17	9.52	4.31	6.47	5.54	-0.14	2.32
Exc. Kurt.	5.36	125.37	56.80	100.42	118.80	0.43	20.27

3.2. Intraday range (IDR)

Realized measures, like realized variance and IDR, are often used as valid proxies for measuring volatility in high frequency, financial data (see: Hansen and Huang, 2016; Hansen, Huang, and Shek, 2012; and Ullrich, 2012). Following Frömmel, Han, and Kratochvil (2014), I apply an IDR calculation to measure volatility in the hourly prices of the seven markets for which data was collected. The IDR is calculated by simply measuring the difference between the maximum price and minimum price within a given day:

$$intraday\ range_t = (\max p_t - \min p_t), \qquad t = 1, \ldots, T \tag{4}$$

where $\max p_t$ is equal to the maximum price within day t and $\min p_t$ the minimum price within day t. For each market, IDR values are calculated over the original price series and an indexed price series, where the price at hour 17 of May 2, 2015 – a peak hour in a month with moderate temperatures for which there is data for all seven markets – is set equal to \$(€)100/MWh. The mean values of the seven hourly price series are different and indexed prices are used to standardize differences in scale of price movements across the series.

Table 3 shows mean, median, maximum, and minimum values of the IDRs for the seven markets, over original and indexed prices of both raw and seasonally corrected price data. High (low) mean and median IDR values indicate high (low) volatility.

A comparison of the IDR statistics across the seven markets suggests that the width of a market's imposed price bounds, as detailed and explained in Section 2, is a fairly reliable predictor of market volatilities: tight (wide) imposed price bounds generally correspond to low (high) IDR values. Volatility of the OMIE market, considered to have the "tightest" price bounds, is consistently among the three lowest while Nord Pool volatility is consistently the lowest. The ERCOT and PJM markets, two of the three "widest" price bound markets, exhibit two of the three highest volatilities.

Table 3: Intraday Range, A.) Hourly, raw B.) Hourly, seasonally corrected

A.)	**CAISO**	**ERCOT**	**MISO**	**PJM**	**Nord Pool**	**OMIE**	**EPEX Spot**
Original series							
mean	27.72	61.52	38.39	44.36	14.70	28.25	42.10
median	24.91	32.22	28.61	35.18	9.61	25.12	32.57
max	461.17	2611.84	264.00	754.98	1361.43	137.93	2405.63
min	7.26	5.93	4.32	6.12	0.60	0.00	5.91
Indexed series							
mean	72.89	126.07	300.31	143.53	63.17	102.72	346.24
median	65.49	66.02	264.55	113.83	41.30	91.33	267.85
max	1212.77	5352.13	2449.70	2443.00	5850.58	501.56	19783.14
min	19.09	12.15	43.50	19.80	2.58	0.00	48.60
B.)	**CAISO**	**ERCOT**	**MISO**	**PJM**	**Nord Pool**	**OMIE**	**EPEX Spot**
Original series							
mean	18.88	62.61	32.50	37.22	13.16	21.79	32.97
median	16.04	37.79	24.05	27.69	8.91	18.82	24.09
max	450.99	2572.76	248.14	738.69	1356.34	125.22	2384.00
min	4.84	7.21	7.07	9.76	2.62	5.09	7.41
Indexed series							
mean	54.71	1318.20	252.96	267.50	47.20	58.58	396.00
median	46.49	795.72	187.23	199.00	31.95	50.60	289.34
max	1306.86	54170.66	1931.37	5309.15	4864.07	336.62	28635.57
min	14.04	151.82	55.05	70.15	9.39	13.69	89.06

Volatilities of the EPEX Spot and MISO markets fall within these two extremes. The Nord Pool market, for example, perhaps owes its consistently low IDR values to its tight price bounds, greater market and consumer homogeneity, greater homogeneity of temperatures in the market region, and its being a pool design rather than an exchange. The CAISO market, however, regularly exhibits some of the lowest volatilities as measured by IDR values despite its having wide price bounds. Conclusions hold over original and indexed raw and corrected prices, suggesting robustness.

Yet, given imperfections of the IDR measure outlined by Patton (2011) and the remaining ambiguity concerning the relationship between price bounds and volatility I apply ARMA-EGARCH(1,1) models in the following section to better measure price behavior.

4. Exogenous Price Bound Changes, ARMA-EGARCH(1,1) Model, and Discussion

At different points in time across the data, market regulators in the EPEX Spot, PJM, and ERCOT markets widened the space in which prices are offered and set both as a reaction to and to encourage changing market dynamics. EPEX Spot market regulators argue that lowering the LMP price floor to allow for negative prices made the market more efficient, via more accurate price signals, and incentivized inflexible producers to invest in flexible production means like renewables. PJM and ERCOT market regulators increased EO price ceilings in reaction to an increase in the occurrence of unusually high demand periods and rising fuel costs such that previous price bounds had become outdated.[4]

I examine these three particular markets namely because regulators introduced known and pronounced, though of different scale and type, exogenous changes to price bounds. They are also some of the largest and most liquid electricity markets in the sample meaning that conclusions about the effects of price bound changes in these markets are more likely to hold in other markets as well.

Exogenous price changes naturally segment price data such that price dynamics can be measured before and after the price change. The following price bound changes, shown in Table 4, were exogenously imposed by market regulators:

[4] See: *Negative Prices: Q&A* prepared by EPEX Spot; FERC Order *PJM Interconnection, L.L.C.*, 153 FERC ¶ 61,289, Docket No. ER16-76-000

Table 4: Exogenous Price Bound Changes

Market	Date	Dummy	Price Bound Change
EPEX Spot	01-Jan-08	*dummy_exog1*	Negative prices introduced
PJM	11-Dec-15	*dummy_exog1*	Energy Offer Cap increased from $1,000/MWh to $2,000/MWh
ERCOT	01-Aug-12	*dummy_exog1*	Energy Offer Cap increased from $3,000/MWh to $4,500/MWh
	01-Jun-13	*dummy_exog2*	Energy Offer Cap increased from $4,500/MWh to $5,000/MWh
	01-Jun-14	*dummy_exog3*	Energy Offer Cap increased from $5,000/MWh to $7,000/MWh
	01-Jun-15	*dummy_exog4*	Energy Offer Cap increased from $7,000/MWh to $9,000/MWh

4.1. Methodology

The exponential GARCH model (EGARCH), a variation of the GARCH classification of models (Bollerslev 1986), was introduced by Nelson (1991) to model the conditional variance and mean of series, typically financial time series, which exhibit heteroskedastic behavior. Following Bowden and Payne (2008), Knittel and Roberts (2005), Frömmel, et al. (2014), and Liu and Shi (2013), I employ the EGARCH specification because it appropriately captures the non-constant variance, non-linear volatility behavior, and inverse leverage effect in electricity prices.

4.2. Model specification and estimation: mean and conditional variance, ARMA-EGARCH(1,1)

I indicate $price_{corrected_t}$ as the seasonality-corrected price on day t with a deterministic and stochastic component:

$$price_{corrected_t} = E\left(price_{corrected_t} | \Omega_{t-1}\right) + \varepsilon_t \tag{5}$$

The deterministic component, $E\left(price_{corrected_t} | \Omega_{t-1}\right)$, explains the electricity price on day t based on information known in time $t-1$. The deterministic component follows an ARMA process:

$$E\left(price_{corrected_t} | \Omega_{t-1}\right)$$

$$= c_0 + \sum_{i=1}^{k} \theta_i dummy_i + \sum_{j=1}^{r} \delta_j dummy_{exog_j} + \varphi_1 price_{corrected_{t-1}} + \sum_{p=6}^{9} \varphi_p \, price_{corrected_{t-p}} + \rho_1 \varepsilon_{t-1} + \rho_2 \varepsilon_{t-7} \quad (6)$$

where c_0 is a constant term, θ_i is a parameter for k number of Bai-Perron breakpoint dummies (explained below) in the price series, δ_j is a parameter for r number of exogenous price change dummies as specified in Table 4, $\varphi_1, \varphi_6 \dots \varphi_9$ are parameters on autoregressive terms, and ρ_1 and ρ_2 are parameters on moving average terms. This ARMA specification agrees with previous studies (Frömmel, et al., 2014; Liu and Shi, 2013; Bowden and Payne, 2008) and accounts for remaining seasonality components in the price which were not captured via the seasonality correction applied above in Section 3.1.

The stochastic component, ε_t, is modeled as:

$$\varepsilon_t = \sigma_t z_t \quad (7)$$

where the innovation process z_t is a Gaussian white noise process with mean zero and variance equal to one. The ARMA-EGARCH(1,1) specifies the conditional variance of ε_t as:

$$\log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \alpha \left(\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - E \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| \right) + \gamma \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right) + \sum_{i=1}^{k} \theta_i dummy_i + \sum_{j=1}^{r} \delta_j dummy_{exog_j} \quad (8)$$

where ω represents the mean of the conditional variance equation, θ_i the impact of the i^{th} of k total number of breakpoint dummies on the volatility of the price series, δ_j the individual effect of the j^{th} of r total number of exogenous price change dummies on the conditional variance, β the degree of volatility persistence, α the amount by which volatility increases regardless of whether a shock is positive or negative, and γ the asymmetric effect coefficient, whereby if $\gamma > 0$ an inverse leverage effect is present in the series.

Equation (5) is referred to as the "mean equation" and Equation (8) the "conditional variance equation."

4.3. Dummy variables: exogenous price bound changes, Bai-Perron

The first of two classes of dummy variables in the mean and conditional variance equations captures exogenous changes to price bounds listed in detail above in Table 4, where $dummy_{exog_j}$ takes a value of 1 beginning on the day, and continues for the remainder of the series, on which the j^{th} exogenous price bound change was implemented. The second class of dummy variables, following Bai-Perron (2003), is estimated by regressing the price series on a constant term using least squares estimation with breakpoints to determine the number and point in time of structural breaks in the series where $dummy_i$ takes a value equal to 1 beginning on the day on which the i^{th} breakpoint was identified to have begun. Bai-Perron dummy variables improve model specification, thereby adding robustness to conclusions drawn about the role of exogenous change dummy variables.

4.4. Data frequency, stationary, treatment of outliers, and residual distribution

Daily price data in levels, versus hourly data, maintains the volatility dynamics of the prices but with less noise and fewer outliers, thereby improving the performance of the EGARCH specification. Daily price data, corrected for weekday and monthly seasonality as explained in Section 3.1., is therefore used.

Augmented Dickey-Fuller unit root tests (Dickey and Fuller, 1981) on the levels of daily price data for all three markets reject the null hypothesis that the series have unit roots, indicating that each price series is stationary and that the EGARCH model can be applied. This suggests a mean-reverting tendency in electricity prices.

Because outliers are so few and pose little threat of biasing parameter estimates, I follow Garcia, Contreras, van Akkeren, and Garcia (2005) and do not correct for outliers in the daily data for the EPEX Spot market. I do, however, set extreme price values equal to the 99.9th percentile in PJM and ERCOT market price data given the more frequent extreme outliers in these series.

I impose the *Student's t-distribution* for the distribution of the residuals of the price series process because it more efficiently captures the fat tails that are consistent with the distribution of wholesale electricity prices. This agrees with Hua, Li, and Lizi (2005) and Huisman and Huurman (2003). I also apply methods following Bollerslev and Wooldridge (1992) to ensure heteroscedasticity robustness and consistency in quasi-maximum likelihood coefficient covariance matrices and standard errors in the models over EPEX Spot and ERCOT price data, though not for the PJM model where residuals exhibit homoscedasticity.

The three ARMA-EGARCH(1,1) models are estimated using maximum likelihood estimation with the EViews statistical package. Results are presented below in Table 5, followed by a discussion of relevant conclusions. Breakpoint dummy variables and autoregressive terms not significant in explaining the mean or volatility of prices were dropped from the models.

Table 5: Parameter Estimates, ARMA-EGARCH(1,1) for EPEX Spot, PJM, and ERCOT markets

Mean eqn.	**EPEX Spot**	**PJM**	**ERCOT**
c_0	13.8951 [0.1469]***	44.0098 [2.6100]***	25.6551 [2.0586]***
θ_1	13.2968 [1.5865]***	8.8254 [3.3550]***	-2.8858 [1.2451]**
θ_2	-15.7030 [2.7580]***	-18.5661 [2.8970]***	
θ_3	-12.8897 [1.3195]***		
θ_4		-5.7588 [1.6557]***	
δ_1	23.2125 [2.9506]***	-2.6130 [1.8798]	2.4686 [2.5723]
δ_2			-3.5167 [1.3244]***
δ_3			-0.7627 [1.4148]
δ_4			-5.9242 [2.4967]**
φ_1	0.6588 [0.0076]***	0.7328 [0.0125]***	0.6304 [0.0401]***
φ_6	0.1421 [0.0048]***	0.0402 [0.0081]***	0.1040 [0.0301]***
φ_7	0.1390 [0.0041]***	0.6458 [0.0327]***	0.3006 [0.0370]***
φ_8		-0.5643 [0.0334]***	-0.0903 [0.0269]***
φ_9	-0.0518 [0.0014]***	0.0945 [0.0115]***	-0.0291 [0.0132]**
ρ_1	-0.0528 [0.0089]***	0.2060 [0.0167]***	0.1747 [0.0504]***
ρ_2	-0.0563 [0.0010]***	-0.5675 [0.0363]***	
Variance eqn.			
ω	0.1091 [0.0402]***	0.2052 [0.0354]***	0.1167 [0.0569]**
β	0.8982 [0.0162]***	0.9041 [0.0079]***	0.8885 [0.0155]***
α	0.3042 [0.0308]***	0.2838 [0.0265]***	0.4393 [0.0626]***
γ	0.0273 [0.0135]**	0.2232 [0.0179]***	0.1236 [0.0296]***
θ_1	0.0876 [0.0219]***		-0.0763 [0.0414]**
θ_2	-0.1047 [0.0257]***	-0.0982 [0.0147]***	
θ_3			
θ_4			
δ_1	0.0569 [0.0238]**	-0.0187 [0.0228]	0.0108 [0.0383]
δ_2			0.0996 [0.0358]***
δ_3			-0.0539 [0.0337]
δ_4			-0.0166 [0.0295]
Model			
Adj R^2	0.7112	0.7641	0.4038
d.o.freedom	3.9164	3.9579	2.9378
AIC	6.2948	6.3103	5.8652
ARCH-LM F-stat	0.7433	1.7685	0.0585

*coefficient [(robust) standard error]; 1%***, 5%**, 10%* significance*

4.5. Empirical results: discussion and implications[5]

Parameter estimates and standard errors of exogenous price change variables, the variables of interest, are boxed in Table 5. The exogenous change dummy variable in the EPEX Spot model is positive and significant in both the mean and variance equations, suggesting that the introduction of negative prices in that market in 2008 increased both the mean and volatility of wholesale prices. Results for the PJM market indicate that the decision to increase the EO price cap in 2015 had no effect on either the mean or volatility of prices, given the insignificance of the exogenous change variable in both equations. In the ERCOT market, the exogenous change in June 2013 (δ_2) lowered the mean of prices and increased the volatility, given its negative and significant value in the mean equation and positive and highly significant value in the variance equation, while the June 2015 decision to increase the EO price cap lowered the mean of prices, and had no effect on volatility, given a negative and significant value of δ_4 in Equation 5.

These results suggest that the wider a market's imposed price bounds, as dictated by its combination of LMP and EO bounds, the smaller and less consistent the effect of exogenous price changes are, all else equal. The exogenous price change in the EPEX Spot market – a market with a tight imposed price bound width – was significant and increased the price volatility. The standard deviation of prices in the EPEX Spot market, depicted in Figure 1, is slightly higher in the period after the 2008 exogenous price change. In the PJM and ERCOT markets, two markets with wide imposed price bounds, exogenous price bound changes had either inconsistent effects (ERCOT market), wherein some changes increased volatility and others did not, or no effects on price volatility (PJM market). In other words, a market's

[5] See Appendix A for model output tables and a plethora of other relevant statistical tests

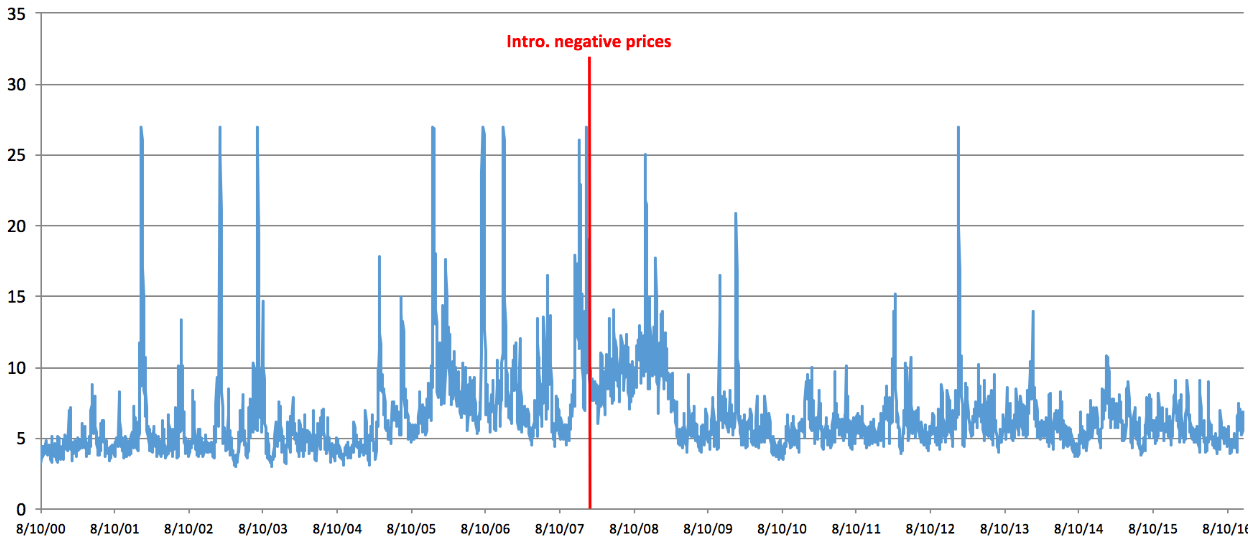
imposed price bounds can to some extent determine the degree to which price bound changes will affect that market's price volatility.

Results also suggest that LMP bound changes have more consistent and greater effects on price volatility than EO bound changes, all else equal. The (significant) exogenous bound change in the EPEX Spot market was made to LMP bounds while the changes in the PJM and ERCOT markets were made to EO bounds. LMP bounds limit final market prices while EO bounds limit auction bids – this difference is likely behind their differing effects on volatility.

Other conclusions might be drawn about the direction of bound changes: the significant LMP bound change in the EPEX Spot market introduced negative prices, while the EO bound changes in the PJM and ERCOT markets increased already-positive price bounds, suggesting that negative bound changes have greater effects on price volatility than positive changes do.

Across all three models, γ is positive and highly significant, confirming an inverse leverage effect in electricity prices noted in previous literature. Moreover, a significant and positive β coefficient close to one indicates high persistence in daily prices across all markets. Degrees of freedom values below four in every model also agrees with past literature that electricity prices exhibit fat tailed distributions different from normal. Significant autoregressive terms indicate that electricity price volatility today is significantly influenced by electricity price volatility in previous days. Low F-statistics on ARCH-LM tests and high Adjusted R^2 values indicate that ARCH effects in the residuals are captured well up to seven lags and that the overall models fit well with the ARMA-EGARCH(1,1) specification, agreeing with Bowden and Payne (2008) and Frömmel, et al. (2014).

Figure 1: Standard deviation in levels (volatility), EPEX Spot market, exogenous price change vertical line, top 0.5% dropped for plot



5. Conclusions and Implications

Using two approaches to measuring volatility in price data for seven wholesale electricity markets in the United States and Europe, this paper adds relevant contributions to early research on the relationship between regulatory-imposed price bounds and price volatility. Results indicate that imposed price bounds are important in determining the degree of price volatility in a market and the degree to which amendments to those bounds affect future price volatility.

Model-free intraday range calculations over the seven markets suggest that the wider a market's imposed price bounds, the greater that market's price volatility. Empirical results from the application of ARMA-EGARCH(1,1) models to price data in the EPEX Spot, PJM, and ERCOT markets offer two important conclusions: that amendments to price bounds have greater effects on volatility in markets where imposed bounds are tighter and that LMP price bound changes have more significant effects on price volatility than do Energy Offer bound changes.

This paper underlines the advantages of using a simultaneous model approach – realized measures and empirical models – to measuring price volatility. It also serves market regulators as they consider the role of price bounds in their markets and, in particular, any changes to those bounds, especially in discussions of price volatility. More generally, conclusions in this paper stress to all market participants, particularly those like risk managers and buyers and sellers who are concerned with price volatility, that price bounds do in fact matter.

Further research should consider more advanced empirical models to better capture jumps and regime switches in price behavior and other exogenous variables like weather forecasts in explaining price volatility.

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